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DB=JPAB,EPAB,DWPI; PLUR=YES; OP=ADJ			
L1	(efficient same portfolio).ti,	0	L1
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L2	(efficient same portfolio).ti.	3	L2

END OF SEARCH HISTORY

Ⓓ List of Databases Searched

Full-Text Databases - Group 1, Descriptions

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Record: 1

Title:	Mean-Value-at-Risk Optimal Portfolios with Derivatives.
Author(s):	Duarte, Jr., Antonio Marcos Alcantara, Silvia Dos Reis
Source:	Derivatives Quarterly; Winter99, Vol. 6 Issue 2, p56, 8p, 1 chart, 5 graphs
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Subject(s):	*PORTFOLIO management *DERIVATIVE securities Evaluation
	NAICS/Industry Code(s)52392 Portfolio Management
Abstract:	Reports a study which proposed the Markowitz's mean-variance (MV) portfolio optimization methodology in the development of modern portfolio theory. Algorithm to generate the MV value at risk efficient frontier; Numerical examples for MV methodology; Conclusion.
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MEAN-VALUE-AT-RISK OPTIMAL PORTFOLIOS WITH DERIVATIVES

Markowitz's mean-variance (MV) portfolio optimization methodology is a landmark in the development of modern port folio theory (Markowitz [1959]). However, five decades later, with several works published illustrating the difficulties of using the MV methodology in practice (Chopra [1993], Michaud [1989]), other alternatives are being used to substitute for it. Among these, we point out the mean downside risk portfolio optimization methodology (Fishburn [1977], Harlow [1993]), and the mean absolute deviation portfolio optimization methodology (Konno and Yamazaki [1991]).

The MV optimization of portfolios with derivatives is a particularly difficult task. For example, the asymmetric returns of options and financial instruments with embedded options require the use of asymmetric risk measures (Lewis [1990], Marmer and Ng [1993]). Controlling leverage when optimizing portfolios with derivatives is also a difficult task (Pogue [1970]). If we add to the asymmetry of returns and leverage control the need to optimize large-scale portfolios with derivatives, we finally get a real-world idea of the problem (Duarte and Maia [1997]).

The MV methodology is the starting point when trying to understand market risk measurement methodologies used in financial institutions, such as J.P. Morgan's RiskMetrics Trademark (see "RiskMetrics Trademark" [1995]). This methodology is used to estimate the value at risk (VAR) of portfolios (Jorion [1997]).

There are basically two approaches to measuring the VaR of portfolios: the analytical approach and the simulation approach. The analytical approach is a straightforward application of the risk measurement methodology embedded in the MV methodology. J.P. Morgan's RiskMetrics Trademark relies on the analytical approach. Analytical methods are not recommended when estimating the VaR of portfolios with asymmetric returns (Beder [1995]), however. Simulation methods are favored here (Jorion [1997]).

Is there a portfolio optimization methodology that plays an equivalent role for the simulation approach to that played by the MV methodology for the analytical approach? Except for the very specific problem of optimal hedge (Duarte [1998]), the answer provided by the finance literature is negative. We propose a portfolio optimization methodology here that provides a positive answer to this question. We propose a methodology that:

1. For a given level of expected return, finds the optimal portfolio that minimizes the VaR measured using the simulation approach.
2. For a given level of VaR measured using the simulation approach, finds the optimal portfolio that maximizes the expected return.

The set of all optimal portfolios that satisfy the two requirements above is what we call the mean-value-at-risk (MVaR) efficient frontier. We call the methodology proposed in this article the MVaR portfolio optimization methodology.

Before proceeding any further, it is important to differentiate between the following two problems:

1. Estimating the VaR of a portfolio using the simulation approach. Risk management groups in several financial institutions do this in their daily routine. This is the statistical problem of estimating a percentile of the probability density function of the expected returns for a given portfolio.
2. Generating the MVaR efficient frontier. This is the problem we are interested in here. It combines the statistical problem mentioned above with the optimization problem of obtaining a portfolio that 1) minimizes the investor's VaR measured using the simulation approach for a fixed level of expected return, and that 2) maximizes the expected return for a given level of VaR. measured using the simulation approach.

One should observe that the second problem is much more difficult than the first problem. Some of the reasons are:

1. While in the first case the portfolio is given (that is, it is known), in the second case it must be optimally structured (that is, it must be obtained) according to the investor's interests.
2. While in the first case the VaR is estimated only once, in the second case it needs to be estimated continuously, during the optimization phase, in order to guarantee that it is equal to the VaR the investor desires, at the end of the optimization phase.
3. In order to generate an approximation to the MVaR efficient frontier it is necessary to structure several optimal portfolios, one for each level of VaR desired.
4. The second problem is much more computationally intensive, resulting in a stochastic programming problem (Ziemba and Vickson [1975]), which we solve using a scenario-based approach (Crum et al. [1979], Nemhauser et al. [1989]) combined with mixed integer linear programming (Murty [1976]).

This article is divided as follows. The next section presents the algorithm used to generate an approximation to the MVaR efficient frontier. Numerical examples taken from the Brazilian stock and derivatives markets are used to illustrate the practical use of the proposal. Finally, the appendix contains the rigorous mathematical formulation of the MVaR portfolio optimization model for those interested in reproducing our proposal in their daily routine.

AN ALGORITHM TO GENERATE THE MVAR EFFICIENT FRONTIER

The Critical Line Algorithm (King and Jensen [1991], Markowitz et al. [1992,1993]) can be used with the optimization model given in the appendix to generate an approximation for the MVaR efficient frontier.

An alternative (which we prefer) is to use the following algorithm to obtain an approximation with p optimal portfolios (p > 2) for the MVaR efficient frontier (see also Duarte [1999]).

Algorithm to Approximate the Efficient Frontier:

Step 0: Initialize all parameters of the optimization model given in the appendix.

Step 1: Maximum Return Portfolio. Obtain the maximum return efficient portfolio by optimizing the model (A-l) given in the appendix with $\text{Gamma}_1 = 0$ and $\text{Gamma}_2 = 1$. Store the output of the optimization model. Define $\text{Rho}^{max} = Z^*$, where $Z]^*$ is the optimal value found for Z (see the appendix).

Step 2: Minimum-Risk Portfolio. Obtain the minimum risk efficient portfolio by optimizing the model (A1) given in the appendix with $\text{Gamma}_1 = 1$ and $\text{Gamma}_2 = 0$. Store the output of the optimization model. Define, $\text{Rho}^{min} = Z^*$ where Z^* is the optimal value found for (see the appendix).

Step 3: Intermediate-Risk Portfolios. For each q is an element of {1, ..., p - 2}, optimize the model (A-1) given in the appendix with $\text{Gamma}_1 = 1$, $\text{Gamma}_2 = 0$, and $\text{Rho} = \text{Rho}^{min} + q[(\text{Rho}^{max} - \text{Rho}^{min})/(p - 1)]$, after adding the constraint

(1) Z >/= Rho

to (A-1). Store the output of the optimization model for each value of q.

At the end of this algorithm, p MVaR efficient portfolios will be available, producing an approximation with p points for the MVaR efficient frontier. For each optimal portfolio on the MVaR efficient frontier, its expected return, VaR measured using the simulation approach, and optimal allocation will be made available for the user by the methodology described.

It can be observed that each optimization model that needs to be solved in Step 1, Step 2, and Step 3, is a mixed-integer linear programming problem. There are several commercial optimization software available today to solve these problems, all of which provide very efficient solutions from the computational point of view (see Duarte [1994] for computational comparisons). The numerical examples presented later were obtained using the optimization software CPLEX 4.0 (CPLEX [1997]) combined with the mathematical programming language GAMS (Brooke et al. [1992]).

The use of commercial software to generate MVaR efficient frontiers illustrates that the practical implementation of the portfolio optimization methodology proposed in this work is not difficult.

The next section presents real-world numerical examples taken from the Brazilian stock and derivatives markets.

NUMERICAL EXAMPLES

In the numerical examples presented we use:

1. One thousand scenarios generated using a Monte Carlo simulation approach (Jorion [1997]), assuming a holding period of one week. These generated scenarios rely only on historical data. It is possible to incorporate the investors' opinion as presented in Koskosidis and Duarte [1997].
2. Fifteen stocks and four derivatives. The stocks used were the fifteen stocks most negotiated in Brazil between 1995 and 1998. The four derivatives were: 1) futures contracts on the Sao Paulo Stock Exchange index, 2) at-the-money plain vanilla call options available at the Sao Paulo Stock Exchange on the most negotiated Brazilian stock (Telebras PN), 3) at-the-money plain vanilla put options on Telebras PN available at the Sao Paulo Stock exchange, and 4) at-the-money plain vanilla call options on Vale PN available at the Rio de Janeiro Stock Exchange.
3. Cash-equivalent instruments are one-week certificates of deposit on Brazilian interest rates.
4. The total amount available for investing is R$50 million or RS 100 minion. (The exchange rate Brazilian real/American dollar was at R$1.20/U.S. $1 the day the numerical examples were obtained.)
5. The probability of all scenarios equals 1/1,000.
6. The minimum and maximum amount to be kept in cash-equivalent instruments are (5%, 100%) or (5%, 25%).
7. The systematic risk (beta) of the stocks is calculated with respect to the most important Brazilian stock index: the Sao Paulo Stock Exchange index.
8. The maximum leverage allowed is 5%, 15%, or 25%.

Exhibit I presents three MVaR efficient frontiers. These were obtained for three levels of maximum leverage (5%, 10%, and 15%), cash-equivalent restricted between 5% and 25% of a total amount available for investing of R$100 million, and a level of significance (for the VaR) of 1%.

Exhibit 1 can be used to analyze the impact of different levels of maximum leverage on the shape of the efficient frontiers. The most aggressive MVaR efficient portfolios are those on the upper left corner of Exhibit 1. For example, on the MVaR efficient frontier which allows a maximum leverage of 25%, the VaR (for a holding period of one week and a significance level of 1%) of the most aggressive portfolio is approximately-14.0%. This is also the portfolio that maximizes the expected return. On the other hand, the most conservative MVaR efficient portfolios are those on the lower right corner of Exhibit 1. For example, on the MVaR efficient portfolio, which allows a maximum leverage of 5%, the VaR of the most conservative portfolio is approximately-0.5%. This is the portfolio with the minimum expected return. Exhibit 1 depicts the gains (in terms of expected return) for allowing more leveraged portfolios.

Exhibit 2 depicts two MVaR efficient frontiers. These were obtained for two significance levels (1% and 5%), a maximum leverage of 5%, cash-equivalent instruments constrained between 5% and 25% of a total amount available for investing of R$100 million.

Exhibit 2 can be used to analyze the impact of different significance levels on the shape of MVaR efficient frontiers. We observe that for any fixed level of expected return, the MVaR efficient frontier obtained with a significance level of 1% is placed on the left of that obtained with a significance level of 5%. Also note that the MVaR efficient frontier obtained with a significance level of 5% is "more curved" than that obtained with a significance level of 1%.

Exhibit 3 depicts two MVaR efficient frontiers. These were obtained for two maximum amounts available for investing in cash-equivalent instruments (25% and 100%), one minimum amount available for investing in cash-equivalent instruments, a total amount of R$100 million available for investing, a maximum leverage of 5%, and a significance level (for the VaR) of 5%.

Exhibit 3 can be used to analyze the impact of different constraints for investing in cash-equivalent instruments on the shape of the MVaR efficient frontiers. As would be expected, the less-constrained MVaR efficient frontier (that is, the one that allows up to 100% in cash-equivalent instruments) lies above the more constrained efficient frontier (the one that allows up to 25% in cash-equivalent instruments) for any fixed level of expected VaR. This is because, for a fixed level of VaR, the set of optimal portfolios that generate the more constrained MVaR efficient frontier is only a subset of the set of optimal portfolios that generate the less-constrained MVaR efficient frontier.

Also, note that the gains from being able to invest larger amounts in cash-equivalent instruments are only marginal when the two efficient frontiers in Exhibit 3 are compared (that is, for a fixed level of VaR, the increase in expected return is small).

An interesting question at this point is related to the MVaR efficient portfolio allocations. As mentioned previously, all numerical examples presented here allowed investments in fifteen stocks, three stock options (two calls and one put), and futures contracts. Exhibit 4 depicts the shape of the distributions of returns of two MVaR efficient portfolios. The two portfolios are the maximum return and the minimum-risk MVaR efficient portfolios on the efficient frontier, which allows a maximum leverage of 25% in Exhibit 1. A comparison between these two graphs reveals that:

1. The distribution of returns of the minimum-risk portfolio is more concentrated around its expected return than the distribution of returns of the maximum return portfolio.
2. The expected return of the minimum-risk portfolio is smaller than the expected return of the maximum return portfolio. This can be explained by remembering that the minimum-risk portfolio completely disregards the expected return while minimizing VaR. On the other hand, the maximum return portfolio completely disregards VaR while maximizing the expected return.
3. The distribution of the minimum-risk portfolio presents a symmetric "bell shape" around its expected return, while the distribution of the maximum return portfolio presents an asymmetric shape, skewed toward negative returns. To understand the shapes of the two distributions of returns, consider their portfolio composition. The minimum-risk portfolio positions itself on cash-equivalent instruments, stocks, and futures contracts, all of which have (approximately) symmetric distributions. That is, the minimum-risk portfolio does not buy or sell options, which present asymmetric distributions of returns. The maximum return portfolio, on the other hand, buys the stock with the largest expected return and sells a certain amount of the only call option with a negative expected return, also leveraging the portfolio to the maximum level allowed (25%).

We also experimented with different total amounts available for investing: R$50 million and R$100 million. The results obtained in these two cases did not show any significant differences.

CONCLUSION

This article presents a portfolio optimization methodology that uses value at risk estimated using simulation methods as its risk measure. We discussed important operational aspects: the mathematical formulation, an algorithm to generate efficient frontiers, computer implementation issues, and numerical examples illustrating its practical use. The resulting methodology is theoretically sound, easy to implement, reliable for use on a continuous basis, and computationally efficient.

The numerical examples illustrate the output provided by the methodology for different parameters, such as maximum leverage permitted, significance level for the estimation of the value at risk, maximum/minimum investment allowed in cash-equivalent instruments, and the total amount of funds available for investing.

Finally, although we restrict ourselves in this article to the mathematical formulation used in the numerical examples, it is straightforward to extend it to more general cases (such as those including transaction costs, constraints for group of securities, borrowing/lending, and so on).

GRAPH: EXHIBIT 1; Mean Value-at-Risk Efficient Frontiers for Different Levels of Maximum Leverage (Theta$_1$ = 5%, Theta$_2$ = 25%, t = R$100 million)

GRAPH: EXHIBIT 2; Mean Value-at-Risk Efficient Frontiers for Different Significant Levels (Theta$_1$ = 5%, Theta$_2$ = 25%, t = R$100 million, Eta = 5%)

GRAPH: EXHIBIT 3; Mean Value-at-Risk Efficient Frontiers for Different Levels of Significance (t = R$100 million, Eta = 5%)

GRAPHS: EXHIBIT 4; Distribution of Returns of Two Mean Value-at-Risk Efficient Portfolios

EXHIBIT 5 Statistics of the Optimization Model

Legend for Chart:

A - Type
B - Amount

A	B
Constraints	
Equality	m + 3
Inequality	m + 4
Total	2m + 7
Variables	
Continuous and Non-Negative	1
Continuous and Free	m + 2
Integer and Non-Negative	$n^{(S)}$
Integer and Free	$n^{(D)}$
Binary	m
Total	2m + $n^{(S)}$ + n[sup D) + 3

Parameters

Total	$mn^{(S)}$ + mn[sup (D) + 2m +	
$3n^{(S)} + 5n^{(D)} + 11$		

ENDNOTE

(*) We define VaR as the largest solution 8 of the inequality

$Pr\{X_{\text{Delta t}}$ < Delta} </= Alpha

where $X_{\text{Delta t}}$ is a random variable denoting the return of the portfolio for a holding period Delta t, the significance level is Alpha t, and Pr{.} denotes a probability measure. It is usual in the finance literature to define VaR to be the absolute value of Delta, as done in Jorion [1997] and "Risk Metrics Trademark" [1995].

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APPENDIX

Optimization Model

The portfolio optimization model presented here is the one used to obtain the MVaR efficient frontier in the numerical examples. It is possible to extend this model to cover more general formulations (as listed above). The extension should be an easy exercise if the reader understands the model presented next, however.

The model is

Maximize: Gamma$_1$V + Gamma$_2$Z Subject to:

(A-1) [Multiple line equation(s) cannot be represented in ASCII text]

where:

1. The number of scenarios used is m.
2. The assets are divided into two classes: stocks and derivatives. The number of stocks is $n^{(S)}$, while the number of derivatives is $n^{(D)}$.
3. The amount invested in cash-equivalent instruments is C. The constraint

(A-2) C >/= 0

enforces that no borrowing is allowed.

- 4. The expected return on one round lot of the i-th stock according to the j-th scenario is $r^{(S),\ \mathrm{sub}\ ij}$. The expected return on one round lot of the 1-th derivative according to the jth scenario is $r^{(D),\ \mathrm{sub}\ 1j}$. Finally, the expected return on cash-equivalent instruments according to the j-th scenario is $r^{(C),\ \mathrm{sub}\ j}$.
- 5. The number of round lots of the i-th stock to be bought is $H^{(S),\ \mathrm{sub}\ i}$. The constraint

(A.3) $H^{(S),\ \mathrm{sub}\ i}$ is an element of {0, 1, 2, ...} Universal quantifier i = 1, 2, ..., $n^{(S)}$

enforces that round lots can only be bought, and that no short sales are allowed for stocks. Similarly, the number of round lots of the 1-

th derivative to be bought or sold is $H^{(D), \text{sub } 1}$. The constraint

(A-4)

(A.3) $H^{(D), \text{sub } 1}$ is an element of {..., -2, -1, 0, 1, 2, ...} Universal quantifier 1 = 1, 2, ..., $n^{(D)}$

enforces that round lots can be bought or sold in this case. Long positions are related to $H^{(D), \text{sub } 1} > 0$; short positions are related to $H^{(D), \text{sub } 1}) < 0$.

- 6. The expected return of an optimal portfolio according to the j-th scenario is R_j.
- 7. The price of one round lot of the i-th stock is $p^{(S), \text{sub } i}$. The price of one round lot of the 1-th derivative is $p^{(D), \text{sub } 1}$ Finally, the price of one round lot of the underlying asset of the 1-th derivative is $p^{(U), \text{sub } 1}$.
- 8. The total amount available for investing is t.
- 9. The probability of scenario j is Omega_j. The parameters Omega_1, Omega_2, ... Omega_m satisfy

(A-5) [Multiple line equation(s) cannot be represented in ASCII text]

- 10. The expected return of an optimal portfolio across all scenarios is Z.
- 11. The VaR computed using the simulation approach across all scenarios is V.(*)
- 12. The "flag" variable F_j indicates if the return R_j of the j-th scenario is below the Alpha percentile of the empirical distribution of R_1, R_2, ..., R_m. These are binary variables (Murty [1976]) as required by the constraint

(A.6) F_j is an element of {0, 1} Universal quantifier = 1, 2, ... m

For an optimal portfolio, if $F_j = 1$, it is true that $V > R_j$; if $F_j = 0$, it is true that V </= R_j.

- 13. The parameter Omega plays the role of the "Big M" in optimization models (Luenberger [1984]). It should be set to a very large number. For instance, in our numerical examples, it was equal to Omega = 10^{10}. Choosing a value for the parameter fl requires attention to avoid numerical instability in the optimization phase (Duarte [1994]).
- 14. The minimum and maximum amount to be kept in cash-equivalent instruments is equal to Theta_1 and Theta_2, respectively.
- 15. The systematic risk (beta) of the i-th stock with respect to a local stock index is Beta_1. Similarly, the beta of the underlying asset of the 1-th derivative is $\text{Beta}^{(D), \text{sub } 1}$.
- 16. The delta of the 1-th derivative is $\text{Delta}^{(D), \text{sub } 1}$.
- 17. The maximum leverage allowed is controlled in the optimization model by using a first-order approximation, as given by the two inequality constraints where the parameter Eta appears. This parameter is used to control maximum leverage in the numerical examples.
- 18. The two parameters Gamma_1 and Gamma_2 in the objective function are used to generate the MVaR efficient frontier.

Some statistics describing the size of the MVaR optimization model are given in Exhibit 5.

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Source: Derivatives Quarterly, Winter99, Vol. 6 Issue 2, p56, 8p
Item: 2677726
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Record: 1

Title:	Currency Crashes and Risk Measurement.
Author(s):	Shivakumar, Ram
Source:	Emerging Markets Quarterly; Fall99, Vol. 3 Issue 3, p5, 9p, 1 chart, 9 graphs
Document Type:	Article
Subject(s):	*DEVALUATION of currency *RISK *MATHEMATICAL models *VALUE analysis (Cost control) Measurement
Abstract:	Discusses the collapse of currencies and related risk measurement models. Why currency crashes occur; How to compute the value at risk of a portfolio; Stress-testing of portfolios.
Full Text Word Count:	4159
ISSN:	10932666
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CURRENCY CRASHES AND RISK MEASUREMENT

On July 2, 1997, the Thai baht began what was to be the first of a dramatic series of currency collapses, losing more than 63% of its value against the U.S. dollar during a six-month period. Within a year, the currencies of the Philippines, Malaysia, Indonesia, and Korea also suffered significant depreciations (Exhibit 1).

In August 1998, the collapse of the Russian ruble provoked financial tremors in emerging markets such as Mexico. Less than six months later, the Central Bank of Brazil decided not to peg the value of the real to the U.S. dollar, precipitating a dramatic collapse of the real (see Exhibit 2).

While the decline in the value of a single currency may not have a dramatic consequence for a diversified portfolio of assets, the collapse of several currencies (and other asset prices as well) will. Indeed, the world's investment banks have reported that their total losses during the second half of 1998 alone were as high as $5.25 billion. Some experts view this number as conservative.

First-generation models of risk, such as RiskMetrics Trademark, are designed to measure the worst case loss that a portfolio can experience over a specified time interval with a given probability on the basis of particular assumptions. This includes the assumption that the portfolio distribution is normal and stationary so that important parameters such as mean, standard deviation, and correlation stay constant through time. As is well known, most currencies violate normality and stationarity.

Emerging market currencies most particularly violate these principles.(n1) Indeed, all the currencies in Exhibits 1 and 2 exhibit significant excess kurtosis. Furthermore, key parameters such as volatility and correlation are very unstable during market crashes. As a consequence, simple risk measurement models are unlikely to provide reliable measures of risk during periods of panic.(n2)

Despite the wide publicity that currency crashes have received in the financial press, the implications of such crashes for risk measurement have not received adequate attention. The purpose of this article is to fill this void.

CURRENCY CRASHES

A currency crash is said to occur when a currency experiences a substantial nominal depreciation over a short time interval.(n3) Of course, the words "substantial" and "time interval" are arbitrary and depend very much on the currency, the prevailing currency regime, and recent trends. Furthermore, this definition ignores the possibility that a central bank may raise interest rates to stratospheric levels or expend its international currency reserves to defend its currency.(n4)

Why do currency crashes occur? One view is that only countries with weak economic fundamentals experience a currency crisis. According to this line of reasoning, investors may experience a loss of confidence in countries whose internal (fiscal) and external (current account) balances are unsustainable; whose assets are overpriced; and whose financial markets are beset by distortions. Another view holds that currency crashes occur not because of weak fundamentals but because of a mismatch between a country's

policies and the market's perception of the country's preferred policies.

The spillover of financial panics from one market to another may occur in one of several ways. First, an economic shock in a major country can induce a collapse of asset prices elsewhere. For instance, the increase in real interest rates in the U.S. in the 1980s played a large part in inducing some highly indebted countries to default on their international obligations and ultimately led to the collapse of their currencies.

Second, a currency crisis in one country may have a negative effect on macroeconomic conditions in other countries, thus inducing a currency crisis there. For instance, the currency turmoil in much of Asia after the collapse of the baht is attributed, at least in part, to the fact that the terms of trade of most of these countries were negatively affected by the collapse of the baht.

A third view -- and one that most practitioners subscribe to -- is that contagion occurs because a crash alters global investors' perception of risk in all markets and induces them to make changes in their portfolios. To the extent that a crash reduces liquidity in many markets, especially emerging markets, contagion is exacerbated.

VALUE AT RISK

One of the most popular methods for measuring portfolio risk is value at risk (VAR). VaR is a summary statistic that quantifies the financial risk of a portfolio over a specified time period. It is generally used to approximate the worst case loss a financial institution or corporation can expect to realize from all its financial exposures. Measuring risk using the VaR method allows one to make statements such as "the portfolio is not expected to lose more than $10 million on more than one of the next twenty days."(n5)

To compute the VaR of a portfolio, the distribution of the potential changes in portfolio value must be generated. Once the portfolio distribution has been computed, the VaR is simply the loss in portfolio value associated with a probability level -- usually 5% (see Exhibit 3).

The simplest and most commonly used method for computing the VaR of a portfolio assumes that the distribution of possible changes in the value of the portfolio is normally distributed. The normal distribution is widely used in many empirical applications for several reasons. First, it is very easy to use and to interpret. Second, because the normal distribution is completely characterized by its mean and variance, a link with modem portfolio theory (in which investors have preferences over the mean and variance of portfolio returns) is established. Third, the normal distribution is the limiting distribution for many statistical testing and estimation procedures.(n6)

From the perspective of risk measurement, the normal distribution suffers from at least two limitations. First, because it assumes that portfolio returns have zero skewness -- returns are distributed symmetrically around the mean -- the relationship between skewness and expected return and volatility is ignored. Other things constant, investors should prefer portfolios that are right-skewed to portfolios that are leftskewed. Therefore, assets that make a portfolio's returns more left-skewed should command higher returns, while the opposite should be true for portfolios that are right-skewed.(n7)

Second, the tails of the normal distribution decay exponentially toward zero, thus reducing the likelihood of extreme observations. Once again, the possibility that extreme returns will occur more frequently than the normal distribution should induce investors to be compensated with higher returns.

Empirical evidence from emerging currency markets refutes the contention that returns are normally distributed. Evidence of time-varying skewness is evident in Exhibit 4. Furthermore, it is evident that some of the sample estimates of skewness are significantly different from zero.

Evidence of excess kurtosis is found in Exhibit 5, which reports the frequency with which particular currency exchange rate changes exceed one, two, three, four, five, and six standard deviations. As a basis for comparison, we also report the frequency with which exchange rate changes ought to exceed one, two, three, four, five, and six standard deviations if the currency returns were normally distributed.

What is evident is that the observed proportion of outliers for currency returns is too large to be a normal series. For instance, the frequency with which exchange rate changes ought to exceed one and six standard deviations is 31.73% and 0%, respectively. But, for every emerging currency in Exhibit 5, exchange rate changes exceed one standard deviation less than 31.73% of the time, and exchange rate changes exceed six standard deviations more than 0% of the time. This implies that currency return distributions are peaked and have fat tails; that is, they are leptokurtic.

Now consider what the tendency for extreme movements in currencies is likely to do to calculations of portfolio VaR. Exhibit 6 displays two distributions describing possible changes in portfolio value. Superimposed on the normal distribution curve is a curve representing a leptokurtic distribution (not assumed to be skewed, for expositional purposes).

The addition of excess kurtosis leads to greater probability mass close to the mean and to the tails of the distribution, while removing probability mass from regions intermediate between the tails and the mean of the distribution. That is, that the probability of large moves is increased, while the probability of intermediate moves is decreased.

Assuming that VaR is calculated at the 5% level, notice that the fifth percentile for the peaked distribution lies to the left of the fifth percentile for the normal distribution. This means that the computed VaR with the normal curve will generally underestimate portfolio risk compared to the peaked distribution with fat tails.

The possibility that VaR may be underestimated is consistent with Lucas and Klaassen [1998], who examine the asset allocation consequence of mistakenly assuming that returns are normally distributed when the actual distribution is fat-tailed. Whether VaR will be underestimated is shown to depend critically on a shortfall constraint – the constraint that places a probability limit on the frequency with which actual returns fall below a threshold level. If the shortfall probability is small, the use of a leptokurtic distribution leads to more prudent allocations.

Put another way, this says that the actual VaR estimate will exceed the VaR estimate computed under the assumption that returns are normally distributed. Indeed, Lucas and Klaassen find that the actual VaR estimate may exceed the computed VaR estimate by as much as 30%.

STRESS-TESTING

While many small organizations still rely on the simple risk measurement models, others prepare for disaster scenarios by stress-testing their portfolios. While the term stress-testing is widely used by risk managers, there is no widely accepted definition of what constitutes a stress test. The public comments of risk managers suggest that many financial institutions' stress-testing programs are designed to revalue their portfolios under selected scenarios that represent dramatic price movements that have occurred (historical stress test) or are remotely possible (prospective stress test). While the details of a process vary across institutions, its outcome is expected to be an estimate of the maximum loss that a portfolio will experience should these scenarios occur.

The stress-testing approach is not, however, without limitation. Its chief disadvantage is that it does not identify the probability of extreme outcomes. To the extent that those in charge of making crucial decisions may view extreme outcomes as low-probability events, they may not choose to take stress-testing analysis seriously.

OTHER RISK MEASUREMENT MODELS

Academicians and quantitative analysts have created other risk measurement models to supplement stress-testing. They include, for instance, stochastic volatility models and modified VaR (second-generation) models. Stochastic volatility models, applied to currency markets, hypothesize that the volatility of a currency changes randomly as the currency evolves. Instead of assuming, as standard models do, that the distribution of currency returns at any time is independent of the past, stochastic volatility models assume that the distribution is random and may depend on time and on the currency value.

This approach is motivated by the observation that volatility and currency values are negatively correlated; i.e., as a currency depreciates, the volatility of currency returns rises, thereby increasing the likelihood of extreme moves. When the currency appreciates, volatility drops. The greater the negative correlation, the "fatter" is the left tail of the distribution.

Suitable calibration of stochastic volatility models can generate portfolio return distributions that provide quite good approximations for the fat-tailed distributions. But despite their strengths, stochastic volatility models are not widely used. This is because the models are often difficult to implement and are not easily understood by senior management (see Chriss [1997]).

Modified VaR models make the assumption that while the unconditional distribution of portfolio returns is not normal, some suitably transformed distribution of portfolio returns is normal. Hull and White [1998] demonstrate how one may transform the actual return distribution into a normal distribution. A notable feature of their approach is that users may specify values for the third and fourth (centralized) moments of the actual distribution, thus capturing some of the features of currency crashes. The transformed distribution then permits the user to infer, in the usual way, the worst case loss to the portfolio over a given period of time. This approach has the advantage that risk managers can infer and communicate to top management and others the probability with which losses may occur.

The method used to compute potential losses due to market risk has important implications for regulatory capital. Investment banks are currently required to determine their regulatory capital by multiplying their VaR estimates by a factor of at least three. If banks were to take their estimates of potential losses from stress tests seriously, the capital that they would have to set aside would be enormous, placing even more pressure on them to take risks in order to achieve higher returns. If they were to use simple VaR models, though, they would be unprepared to withstand crashes.

OPTION RISK

Currency crashes have important implications for the pricing and measurement of option risk. Consider, for instance, plain vanilla currency options. The standard practice in the industry is to price these options using the Garman-Kohlhagen (GK) model (the Black-Scholes model adapted to the currency markets). Using the GK model to price a currency option requires the user to provide the current spot price, the strike price, the domestic and foreign risk-free rates of interest, the time to expiration of the option, and the volatility of the underlying currency. Alternatively, given the market price of the option, one may compute the implied volatility that makes the market price equal to the theoretical price using the GK model. This volatility is known as implied volatility.

A feature of interest is the volatility smile, which describes the way the implied volatility of a specific option varies with the strike price, given a fixed time to expiration. The GK model says that the implied volatility of options with different strike prices, but having the same underlying currency, must be the same. In other words, the curve is fiat. But as is well known, the empirical evidence shows that the curve is not fiat. It often resembles a smile – the implied volatility of deep out-of-the-money and deep in-the-money options is higher than the implied volatility of at-the-money options (see Exhibit 7).(n8)

To see how a currency crash may be expected to influence implied volatilities of options, consider Exhibit 8, which plots the postcrash relationship between implied volatility and strike prices (as a percentage of spot). Notice that this postcrash relationship is different from the pattern observed before the crash. Instead of a smile, we observe a sneer – the implied volatility of the call (put) option decreases monotonically as the call (put) option goes deeper out of the money (in the money).(n9)

The accentuation of the volatility smile has serious consequences for risk mitigation. Most option traders determine their hedges based on the computation of the Greeks m delta, gamma, theta, rho, and tau from the GK model. The Greeks, however, will be biased because the formula for computing them is based on the GK model, which assumes that volatility is a constant.

Since the GK model's errors are accentuated during periods of market turmoil, those using the Greeks to hedge their portfolios dynamically will be compounding their errors.(n10)

CREDIT RISK

The measurement of credit risk is one of the most important challenges confronting Wall Street. This challenge has arisen because financial institutions and corporations have recognized that while they have increased their credit exposures at very rapid rates, they have not developed adequate methods for monitoring and controlling credit risks.

Since the mid-1990s, several different credit risk measurement models have been introduced. Perhaps the most well-known credit risk model is the CreditMetrics Trademark model introduced by J.E Morgan in 1996.(n11) Almost all credit risk models are designed to provide a measure of portfolio losses due to changes in security value caused by changes in the credit quality of obligors or the probability of default.

Computing the credit risk of a portfolio, some or all of whose components (securities) are denominated in emerging market currencies, involves three steps. The first step is to construct a credit rating migration distribution for each security. This distribution tells us with what probability a firm with a given credit rating will transit to another credit rating or default. The second step is to compute a probability distribution of returns for this security, given its credit rating.

The third step is to compute the portfolio return distribution. To perform this step, one needs to compute the joint likelihood of observing each security's credit rating at a given level and the resulting effect on returns. Since any two securities' credit ratings are not likely to be independent, the correlation between ratings is needed to derive an accurate portfolio distribution.

Once the portfolio distribution is obtained, the credit risk of the portfolio is, according to the VaR approach, the difference between the portfolio's expected retum and the portfolio's return at a 5% confidence level.

A key difference between modeling market risk and modeling credit risk is that credit risk distributions are not assumed to be normally distributed. As Exhibit 9 shows, credit returns are generally skewed and fattailed. Because there is a fairly large likelihood that a security with a given credit rating (say, BB) will not default, there is a fairly large likelihood of the security earning a small return. But because there is some probability that the firm may default, the probability of substantial losses is small but non-trivial: hence, the skewed distribution with the long left-hand tail.

Now consider the consequence of a currency crash, say, of the Brazilian real, on the computation of the credit risk of a portfolio of international securities. When the real crashes, the market generally responds by downgrading the credit quality of Brazilian firms (or other firms that do substantial business in Brazil) because it perceives them as more likely to default. In addition, the market also may perceive that the credit quality of firms doing business in other emerging markets (such as Mexico) is lower because of the possibility of contagion.

What is this likely to do to the credit return distribution? It will shift to the left (see Exhibit 10). The impact of such a shift is to leave the fifth percentile for the postcrash credit return distribution to the left of the fifth percentile for the precrash credit return distribution. If the shift in the distribution is significant, the VaR of the postcrash retum distribution will be higher than the VaR of the precrash return distribution.

CONCLUSION

Financial institutions and academics have created sophisticated methods to measure potential losses from currency crashes. Most small banks and corporations, however, are relatively unfamiliar with these methods and continue to work with the first-generation risk measurement models. These models are predicated on the assumptions that portfolio returns are normally distributed, and that important parameters such as mean, volatility, and correlation are constant through time.

These assumptions are inadequate for measuring risk in most emerging markets, because many emerging market assets exhibit variation in higher moments such as skewness and kurtosis. Any model that purports to measure emerging market risk accurately must use forward-looking estimates of these higher-order moments.

ENDNOTES

(n1) See Bekaert and Harvey [1997] for a discussion of the statistical properties of emerging equity returns and Shivakumar and Simonsen [1999] for a discussion of the statistical properties of emerging currency returns.

(n2) Large investment banks such as J.P. Morgan, Credit Suisse First Boston, and Lehman Brothers claim that they can predict crashes with reasonable certainty. For instance, J.P. Morgan claims that its "emerging markets risk indicator" would have correctly predicted nine of the last ten currency crashes at least one month earlier. None of these models, however, integrate crash prediction and risk measurement. See Berg and Patillo [1998] for a survey of currency prediction models.

(n3) Frankel and Rose [1996] define a currency crash as a nominal depreciation of at least 25% during a year that follows a year when depreciation was at least 10% lower.

(n4) For a comprehensive discussion of currency crises, see Krugman.

(n5) There are at least three reasons why the VaR methodology has become popular with both financial institutions and corporations. First, it is easy to compute and understand. Second, because it is a probability-based measure, it provides users with the likelihood of potential losses. Third, the VaR methodology makes it possible to compare risks across business units or trading desks.

(n6) For a description of the technical aspects of alternative VaR models, see Jorion [1997] and Duffie and Pan [1997].

(n7) Recent empirical research shows that the main prediction of the single-factor capital asset pricing model (CAPM) that cross-sectional variation in expected returns can be explained by the market beta alone – is invalid. To address the criticism that the classical CAPM ignores higher moments, Harvey and Siddique [1999] develop a theoretical model in which skewness is priced. Applying this model to U.S. equity returns, they find that skewness can explain more of the cross-sectional variation in equity returns than other factors.

(n8) The failure of the Black and Scholes model to adequately describe the cross-section of currency option prices is believed to arise because of the constant-volatility assumption. As has been widely noted, there is an inverse relationship between stock (or currency) prices and volatility -when prices go up, volatility declines, and vice versa. Developing an option pricing model to capture this relationship is, however, a difficult task because of the difficulty of estimating the market price of risk. In the special case in which volatility is a function of prices and time, the Black and Scholes partial differential equation may still be used. Dumas, Fleming, and Whaley [1998] compare alternative deterministic volatility functions that satisfy the Black and Scholes partial differential equation.

(n9) Comparing the volatility smile during the period preceding the crash of 1987 with the volatility smile after the crash of 1987, Rubinstein [1994] found the post-1987 smile to be more accentuated. See Dumas, Fleming, and Whaley [1998] for evidence from S&P index options markets.

(n10) Currency crashes also have important implications for exotic options that rely on estimates of correlation (such as basket options and quantos). To the extent that crashes cause correlation to be measured with greater error, these options will be difficult to price and, as a consequence, hedge.

(n11) Others are CreditKisk+, KMV, and CreditPortfolio View.

GRAPHS: EXHIBIT 1; Daily Spot Exchange Value vis-a-vis the U.S. Dollar

GRAPHS: EXHIBIT 2; Daily Spot Exchange Value vis-a-vis the U.S. Dollar

GRAPH: EXHIBIT 3; Value at Risk at 95% Confidence Level

GRAPHS: EXHIBIT 4; Moving Average Values of Skewness Using Daily Spot Exchange Values

EXHIBIT 5 Percent Changes in Spot Exchange Values in Excess of Given Standard Deviation

Legend for Chart:

B - Baht
C - Won
D - Ringgit
E - Rupiah
F - Chile Peso
G - Real
H - Mexican Peso
I - Ruble
J - Normal

A	B	C	D	E	F
	G	H	I	J	
> 1 Std Dev	14.80	9.72	16.26	12.52	17.84
	18.17	14.39	2.90	31.73	
> 2 Std Dev	4.64	5.01	6.53	4.95	4.35
	5.76	4.01	0.68	4.55	
> 3 Std Dev	1.89	2.50	2.47	3.20	2.10
	2.36	1.34	0.68	0.27	
> 4 Std Dev	1.02	1.47	1.02	2.04	0.90
	1.03	1.04	0.68	0.01	
> 5 Std Dev	0.73	0.88	0.73	1.02	0.60
	0.30	0.45	0.51	0.00	
> 6 Std Dev	0.29	0.59	0.73	0.73	0.30
	0.09	0.15	0.51	0.00	

GRAPH: EXHIBIT 6; Actual VaR in Comparison with Computed VaR Using the Normal Distribution

GRAPH: EXHIBIT 7; Implied Volatility and its Relationship with Strike Prices

GRAPH: EXHIBIT 8; Implied Volatility After a Crash

GRAPH: EXHIBIT 9; VaR for Credit Risk

GRAPH: EXHIBIT 10; VaR for Credit Risk After a Crash

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FORWARD HEDGES THAT INCREASE VALUE AT RISK

In the computer-dominated world of portfolio risk management, value at risk (VaR) has quickly become the "golden apple" which seemingly all industry professionals are reaching for. In many ways, this is understandable. The promise of VaR is quite tantalizing: "List all your assets and, using sound financial and statistical theory, I will quantify your overall risk for you. List only some of your assets, and I will tell you what risk is associated with those in isolation." At this point, many risk managers put their feet up, close their eyes, and dream about the peaceful utopia that would be their risk departments.

Of course, it is true that if all the assumptions underlying a particular VaR, calculation are met, the results will be very useful. Managers will be able to identify, in a quantitative fashion, changes in the level of risk associated with a set of holdings. Further, they may do this long before the risk leads to potential losses.

Something is getting lost in the transition from the "pre-VaR days" to the present, however. Using standard Markowitz portfolio theory, it is easy to show that two assets can hedge each other by virtue of their prices generally moving in opposite directions.(n1) Hedging also can be undertaken by coupling derivatives contracts with underlying investments. For example, the foreign exchange risk of international investments can, in principle, be hedged with contract such as FX forwards. Sometimes, however, foreign exchange forwards appear to be increasing total fund VaR. How could correctly designed hedges actually be increasing the total value at risk?

This article first goes over a brief description of Vill, theory. Later it reviews how forward currency hedges work to reduce the risk of single assets and then describes the way that even a good forward hedge can raise VaR in a portfolio of two or more assets. The next section provides two examples: a portfolio of two foreign bonds, and a portfolio comprised of a US. equity and a foreign bond.

A BRIEF OVERVIEW OF VAR THEORY

Value at risk, or VaR, is a risk measurement methodology first popularized by the Global Derivatives Study Group of The Group of Thirty in 1993. It attempts to answer the question: "What is the least amount of money I can expect to lose in each of the worst 5% of my return periods?" For example, if one tracks the daily returns of a particular portfolio, one would consider the fifth-worst loss out of 100 days to be one's 5% VaR. Now, if the holdings in the portfolio stay relatively constant, and if the general economic conditions that impact the portfolio's value do not change too much, one can reasonably expect to lose more than the calculated 5% VaR in the future 5% of the time. If historical returns are not available or if the holdings in the portfolio change frequently, this method will not work.

The RiskMetrics Trademark methodology, pioneered by J.P. Morgan and implemented with publicly available RiskMetrics data, attempts to get around this problem by making certain statistical assumptions about the distributions of asset returns.(n2) Specifically, RiskMetrics Trademark assumes that asset prices are lognormally distributed and, equivalently, that daily returns (continuously compounded) are normally distributed. Making this assumption, one can calculate the 5% VaR by simply finding the standard deviation of the return series and multiplying it by the relevant cash flow.

The RiskMetrics Trademark data sets provide daily or monthly standard deviations for many asset classes and maturities.(n3) All the standard deviations in the file are already multiplied by 1.65, the number of standard deviations that separates the 5% tail of the normal distribution from the 95% body. Other implementations of the VaR methodology allow the user to define VaR as the return that corresponds to other confidence levels. A risk averse bank manager, for example, might want to monitor the VaR at the 1% level. Using the RiskMetrics Trademark data set, this could be accomplished by multiplying the 5% VaR by (2.33/1.65).(n4)

To make use of the RiskMetrics Trademark methodology and data set, the cash flows on all instruments in a portfolio must be decomposed into elemental cash flows that correspond to the asset classes and maturities for which volatility information is available in RiskMetrics Trademark Consider, for example, a U.S. corporate bond with a face value of $1,000 that pays $50 every six months. If the maturity is one year from now, there would be two cash flows: $50 six months from now and $1,050 in one year. These cash flows can be mapped to their appropriate RiskMetrics Trademark vertices (i.e., asset class and maturity points) either as present values or future values on a cash flow map. Simply put, the cash-flow map is a matrix of currency and asset type combinations. To map an asset into this matrix, one need only drop the component cash flows of the asset onto the appropriate vertex in the matrix.(n5) The cash flow map (using future values and an interest rate of 5.5%) for the $1,000 bond can be seen in Exhibit 1.

We can calculate the three-month, 5% VaR directly. If the correlation between the six-month and one-year cash flows is less than +1, there will be some diversification benefit in the two combined cash flows and the total VaR will be somewhat less than the sum of the two individual cash flow VaRs. The diversified VaR, will reflect this. We know that the standard deviation of a portfolio of two assets is:

Sigma_p = square root of $w^{2,\text{ sub }1}\ \text{Sigma}^{2,\text{ sub }1} + w^{2,\text{ sub }2}\ \text{Sigma}^{2,\text{ sub }2} + 2w_1w_2\text{Rho}_{1,2}\text{Sigma}_1\text{Sigma}_2$

The January 7, 1998 monthly RiskMetrics Trademark data sets gives the following values:

Sigma_1 = one-month standard deviation of R180 cash flow = 0.099291%

Sigma_2 = one-month standard deviation of R360 cash flow = 0.287103%

$\text{Rho}_{1,2}$ = correlation between R180 and R360 cash flows = 0.904255

We need the three-month standard deviations, however. We estimate these by multiplying each one-month standard deviation by square root of 3. The weights we use are 51.36 and 1,050, the future values of the cash flows. This will convert our standard deviation into dollar terms. Because the RiskMetrics Trademark standard deviations are already multiplied by 1.65, our answer will be the VaR we are looking for. Entering these values into the portfolio standard deviation equation yields VaR_p = $5.301. Note that diversification makes this VaR smaller than the sum of the VaRs of the individual cash flows.

Various version of VaR-calculating software works by mapping all assets onto the same cash flow matrix and generating an aggregate expected return distribution.(n6) This final distribution takes into account inter-asset correlations and differing volatilities of assets. The software then simply reads the diversified VaR of a particular confidence level off the distribution.(n7)

HEDGING THE CURRENCY EXPOSURE OF A SINGLE ASSET WITH A FORWARD CONTRACT

The cash flows generated from a FX hedge are intended to be roughly equal in magnitude to the cash flows generated by the assets being hedged. However, these two sets of cash flows will always have opposite signs, as the hedge works by reducing the net cash flow exposure to exchange rate fluctuations. Any loss to the value of the holding because of exchange rate movements will appear as gains to the hedge instrument, and vice-versa. Ideally, these losses and gains should offset each other perfectly.

For example, if one holds a one-month Canadian zero-coupon bond, two major risks exist. The first is the interest rate risk over the next month. This, for a one-month Canadian bond, is negligible compared to the second risk: foreign exchange risk. At the end of the month, the Canadian bond will pay Canadian dollars and not US. dollars. So, one runs the risk that the U.S. dollar Will greatly appreciate against the Canadian dollar. Then, when one converts the Canadian dollars back into U.S. dollars (assuming the US. dollar is the home currency), one will incur a substantial foreign exchange loss. Using current market conditions, roughly 98% of the total VaR stems from the foreign exchange risk.

To manage the risk of exchange rate fluctuations over the life of the bond, one may enter into a foreign exchange forward contract. This forward would be an agreement to deliver a certain number of Canadian dollars in one month for a certain number of U.S. dollars. The number of Canadian dollars to be delivered would be set to be the number of Canadian dollars that one will receive for the Canadian bond in one month. The number of U.S. dollars one would receive would be the USD/CAD forward foreign exchange rate multiplied by the number of Canadian dollars involved. When this contract is created, the contract exchange rate for USD/CAD is fixed.

HOW A GOOD FOREX FORWARD HEDGE CAN BREAK DOWN

In the example from the last section, the forward hedge would work exactly as it was designed. There are no situations in which the VaR of one holding would be increased by the introduction of a properly constructed FX hedge for that holding. If one introduces a second holding to the portfolio, however, the FX hedge can become disadvantageous.

Suppose a portfolio of two foreign holdings is created. Further suppose that the currency of the second holding is negatively correlated with the currency of the first holding. In this case, one has a portfolio that (at least partially) hedges itself. For argument's sake, assume that the correlation between the two currencies is -1 (perfectly negatively correlated) and that the U.S. dollar values of the holdings are equal. If interest rates in the respective countries are equal, the portfolio would be perfectly hedged. This could be called a "natural hedge."

If the two original assets are a perfect natural hedge, the introduction of a FX hedge instrument will have an undesirable effect: it will undo the natural hedge by hedging one of the holdings itself and leave the other holding unhedged. This could be called a "forward mirage," as the benefits of the forward hedge are illusionary. Alternatively, one could think about it this way: because the portfolio is already hedged, the forward contract is simply an outright position in the foreign exchange market.

Obviously, this phenomenon can occur when the correlation between two currencies is larger than -1. Additionally, it can occur with any number of holdings in a portfolio greater than one. The next section's example uses actual currency correlation data found in J.P Morgan's January 7, 1998, correlation and volatility data sets. For the sake of simplicity, only two holdings are used.

TWO EXAMPLES OF DISADVANTAGEOUS HEDGES

Example One: ATS Bond and CAD Bond

Suppose that one has a portfolio containing two holdings:

One-month Canadian Government Bond, Face Value: 1B CAD

One-month Austrian Government Bond, Face Value: 1.1B ATS

At prevailing exchange rates, the Canadian bond holding is worth 695.61 million USD. The Austrian holding is worth 85.42 million USD. Thus, the Canadian holding is roughly four-times the size of the Austrian holding. An examination of the J.P. Morgan January 7, 1998, correlation data set shows that correlation between the CAD and ATS currencies is -0.230348.

The diversified VaRs (calculated using FEA's Outlook Trademark software(n8)) of each holding calculated separately are as follows:

ATS BOND: 5.72 Million USD CAD BOND: 22.21 Million USD

However, because of the negative correlation between the currencies, the diversified VaR of the two-holding portfolio is:

ATS & CAD BOND Portfolio: 21.62 Million USD

This is striking in that the diversified VaR of the portfolio is actually smaller than the diversified VaR of just the CAD bond holding. Exhibit 2 shows the cash flow maps of each bond, the VaRs of each cash flow, and the diversified VaR values.

Now, suppose that one hedges the 1.1 billion ATS holding. This is accomplished by entering into a forward FX contract in which one agrees to deliver 1.1 billion ATS in three months. Suppose the exchange rate used in the forward contract is the current exchange rate, so that one would receive 86.562 million USD in exchange for the 1.1 billion ATS. Of course, this contract exchange rate is an approximation. The correct exchange rate would be given by the formula:

$F = Se^{(r - r[sub f) - t]}$

If one assumes that the foreign interest rate is close to the domestic interest rate, then the spot exchange rate will be close to the forward exchange rate. In the case of this example, the approximation does not affect the results.

The effect of this hedge is that the natural hedge properties of this portfolio are destroyed. Instead of decreasing, the diversified VaR of the portfolio increases from 21.62 million to 22.21 million USD, as can be seen in Exhibit 3.

The increase of VaR is due to an increase of foreign exchange risk. This means that the portfolio is over-hedged, and that the FX hedge is effectively equivalent to speculating in the foreign exchange market. Thus, the FOREX forward was a mirage, and the hedge has failed.

Example Two: USD Equity and FRF Bond

Now suppose that one holds two different asset types in a portfolio. In this example, we will assume that we have a portfolio made up of a $4.5 billion position in the S&P 500 index, and a variable position in a French franc-denominated government bond. We will assume that the bond matures in thirty days. If we are US. investors, there is no currency risk from the equity position. The only risk we face from the equity is the equity return volatility Conversely, almost all of the risk associated with the French bond is due to the fact that it is denominated in francs, not dollars. The risk due to interest rate risk is again negligible.

In this example, the February 17, 1998 J.R Morgan RiskMetrics Trademark data sets are used. The correlation of interest is that between the USD equity and the FRF exchange rate. In this data set, it happens to be -0.265749. We start with a portfolio that only contains the USD equity position. The VaR of this position is roughly $500 million. By slowly adding the French bond to the portfolio, we again reduce total VaR. Exhibit 4 shows that for any investment in French bonds less than roughly $3.7 billion, total portfolio risk is less than what the equity position would have on its own. It can be seen that the minimum portfolio VaR occurs with a bond investment of roughly $2 billion.

Thus, a forward contract that fully hedges French franc exposure will increase VaR back to the equity's original VaR, with the small addition of the bond interest rate risk. The interest rate risk no longer comes from French interest rates. The addition of the forward contract to the foreign bond makes the combined risk and return identical to that of a U.S. bond of equal size (Ihle [1997]).(n9)

SUMMARY AND CONCLUSION

While the idea of correct FX hedges increasing the risk of a portfolio is counterintuitive, certain sets of intra-asset and inter-asset correlations can cause that exact result. When this occurs, the extra currency risk introduced by the forward contract is actually equivalent to a speculative currency position -- at least at the total portfolio level, Wherever natural hedging exists due to negative correlations, total portfolio VaR may be increased due to hedges. This is regardless of the fact that each individual hedge dramatically decreases the risk associated with the single asset it is designed to hedge.

The conclusion of this analysis, then, is that hedging to reduce VaR at a portfolio level is not as effective as it might first appear. Assume we are in an organization with multiple portfolio managers. If the goal is to allow each portfolio manager to hedge some or all of his or her own risk, then one must realize that the total risk of the organization is larger than it needs to be. In fact, the total risk may be larger than the amount that would have existed without any hedging. This, depending on the organization, may be appropriate. For example, if the portfolio managers are trying to provide excess returns due to the amount they are hedged, then this is fine. However, if the organization is interested in hedging foreign exchange risk as a matter of risk management, then a different strategy may be better. The organization should determine its aggregate risk from all portfolios, then use an overlay hedging strategy to minimize its overall risk. This strategy would eliminate the possibility that the total fund is overhedged, effectively taking speculative positions.

In many ways, the results here are no different than the diversification results first noted by Markowitz many years ago. However, the recent fascination with VaR casts an old problem in a somewhat new light. In particular, as institutions begin to track VaR, only a few may see this effect from their forward contracts. This is because only a few are separating-out each asset class to examine its effect on total fund VaR. It is much easier to get a VaR system up and running by just dumping all financial instruments into the same cash-flow matrix from the beginning. But when this is done, one loses the ability to see the incremental effect on VaR of each instrument -- specifically, the incremental effect of adding hedges into each portfolio and then again at the fund-wide level. Losing this ability to examine portfolio risk, aggregate risk, and incremental instrument risk is losing one of the greatest things that VaR analysis has to offer, and institutional investors should be wary.

ENDNOTES

The author is grateful to Ron Mensink for his comments and conversations. The views expressed herein do not necessarily represent the views of SWIB.

(n1) See Markowitz [1991].

(n2) Other methods for computing VaR without presuming a particular distribution also are available but are not discussed in this article.

(n3) The RiskMetrics Trademark data sets can be downloaded from http://www.RiskMetrics.reuters.com

(n4) One must first divide by 1.65 to undo the scaling that is in the RiskMetrics Trademark data set. Then one must multiply the standard deviation by 2.33 to separate the 1% tail of the normal distribution.

(n5) If the cash flows do not fall perfectly onto one of the predefined vertexes, one must split up the cash flow and assign its components to the nearest two vertexes. RiskMetrics Trademark advises doing so by preserving three characteristics of the cash flow: market value, market risk, and sign. For more information, see RiskMetrics Technical Document [1996].

(n6) For a detailed description of this process, see parts 1 and 2 of RiskMetrics Trademark Technical Document, 4th ed., December 1996.

(n7) Diversified VaR is what is described here, because this article is concerned with the effects of hedges on portfolio diversification, as measured by VaR. One may also calculate "undiversified VaR" by finding the VaR of each component of the cash flow map and adding them all together.

(n8) For information on this software contact FEA at (5 10) 548-6200.

(n9) See Ihle [November 1997].

EXHIBIT 1; Cash flow Map of U.S. Bond

Series	USD
R180	51.36
R360	1,050

Here, USD is the column for the U.S. currency.
R180 and R360 denote rows for 180-day and
360-day debt vertices, respectively.

EXHIBIT 2; Cash Flow and VaR Maps of Individual Bonds and Bond Portfolio

ATS Bond

Cash Flow Map

Series	ATS	Total
XS	85.57	85.57
R030	85.57	85.57
SE	0.00	0.00
Total	171.14	171.14

VaR Map

Series	ATS	Total
XS	5.72	5.72
R030	0.04	0.04
SE	0.00	0.00
Total	5.76	5.76

Diversified VaR

5.72

CAD Bond

Cash Flow Map

Series	CAD
XS	697.04
R030	697.04
SE	0.00
Total	1394.09

VaR Map

Series	CAD
XS	22.17
R030	0.40
SE	0.00
Total	22.57

Diversified VaR

22.21

Bond combo Porfolio

Cash Flow Map

Series	Total	Series	ATS	CAD	Total
XS	697.04	XS	85.57	697.04	782.61
R030	697.04	R030	85.57	697.04	782.61
SE	0.00	SE	0.00	0.00	0.00
Total	1394.09	Total	171.14	1394.09	1565.22

VaR Map

Series	Total	Series	ATS	CAD	Total
XS	22.17	XS	5.72	22.17	27.89
R030	0.40	R030	0.04	0.40	0.44
SE	0.00	SE	0.00	0.00	0.00
Total	22.57	Total	5.76	22.57	28.33

Diversified VaR

21.62

EXHIBIT 3 Cash Flow and VaR Maps of Forward Contract and Total

Portfolio

Forward ATS Contract

Cash Flow Map

Series	ATS	CAD	USD	Total
XS	-85.57	0.00	0.00	-85.57
R030	-85.57	0.00	85.52	-0.04
SE	0.00	0.00	0.00	0.00
Total	-171.14	0.00	85.52	-85.61

VaR Map

Series	ATS	CAD	USD	Total
XS	5.72	0.00	0.00	5.72
R030	0.04	0.00	0.04	0.09
SE	0.00	0.00	0.00	0.00
Total	5.76	0.00	0.04	5.80

Diversified VaR

5.71

Forward Contract and BOND Portfolio

Cash Flow Map

Series	ATS	CAD	USD	Total
XS	0.00	697.04	0.00	697.04
R030	0.00	697.04	85.52	782.57
SE	0.00	0.00	0.00	0.00
Total	0.00	1394.09	85.52	1479.61

VaR Map

Series	ATS	CAD	USD	Total
XS	0.00	22.17	0.00	22.17
R030	0.00	0.40	0.04	0.44
SE	0.00	0.00	0.00	0.00
Total	0.00	22.57	0.04	22.62

Diversified VaR

22.21

GRAPH: EXHIBIT 4; USD Equity/FRF Bond Portfolio VaR as a Function of FRF Bond Value ($)

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- *The Almanac of Online Trading: The Indispensable Reference Guide for Trading Stocks, Bonds, and Futures Online*. Terry Wooten. McGraw-Hill Professional Publishing, 2000.
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